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Productivity, scale and efficiency in the U.S. textile industry

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Abstract In this paper we employ panel data techniques to address several issues related to the recent performance of the textile industry. We build on the research and results obtained by Ramcharran (in Empirical Econ 26:515–524, 2001) for the textile industry as a whole, by extending the analysis to the sector level. Using data for 23 sectors over 39 years (1958–1996), we estimate a variable elasticity of substitution (VES) production function; the results allow us to construct time-series of marginal products of inputs and elasticities of scale and substitution. We find evidence in support of the use of a VES function and conclude that there are systematic differences among textile sectors' productivity and performance.

Keywords VES function · Productivity · Textiles · Scale elasticity

1 Introduction

The textile industry contributes nearly $62 billion in output to the US GDP, generates almost $50 billion in spending on goods and services, employs about half of a million workers, and is the third largest manufacturing sector;[1] yet its evolution over the past few decades has been largely neglected in the economics and finance literature. The existing studies deal with such topics as firm entry and exit, declining employment, effects of foreign competition, impacts

[1] *Sources:* American Textile Manufacturers Institute (ATMI), National Council of Textile Organizations (NCTO).

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of different investment strategies, and the role of innovation.[2] The industry is generally viewed as performing at a subpar level relative to other US manufacturing sectors; however, many of these conclusions are based on analysis done at the industry level. Meanwhile, data from the individual sectors of the textile industry and plant-level data paint a very different picture: the industry is undergoing a rebirth of sorts, appropriately called "creative destruction" by Levinsohn and Petropolous (2001).

In this paper, we study the evolution of the production processes of 23 four-digit SIC sub-sectors of the textile industry in an attempt to analyze the changing patterns of scale of operation and input use. Application of econometric techniques to our panel allows us to separate the observed effects into sector- and time-specific trends.

2 Theoretical background

The production functions commonly used to study a particular industry, such as the Cobb–Douglas (CD) or the constant elasticity of substitution (CES) functions, are often deemed too restrictive. Indeed, in the former case, the elasticity of substitution between inputs – typically, capital and labor – is assumed to equal one, while in the latter, it is assumed constant. An alternative approach is to use a variable elasticity function, which allows for the needed flexibility: the substitution elasticity parameter varies with the size of the inputs themselves.

The variable elasticity of substitution (VES) production function, introduced by Hicks (1932) and used by Vinod (1972, 1976) to study the telecommunications industry, and applied to the textile industry as a whole in Ramcharran (2001), can be written as

$$Y_{it} = e^{b_0} K_{it}^{b_1 + b_3 \ln L_{it}} L_{it}^{b_2} \tag{1}$$

The function in Eq. (1) describes production in sector i in period t given the available inputs. This specification assumes constant technology across sectors and also over time, even though the elasticity of substitution is allowed to vary in both dimensions. While this assumption may not be completely innocuous given the differences between textile sectors and the relatively long period under consideration, we feel that the variable-elasticity property of the function in (1) should capture the most relevant changes in the production processes.[3]

[2] See Levinsohn and Petropoulos (2001) for a comprehensive survey of these studies.

[3] To assess this issue further, we attempted to estimate a random coefficients model (RCM) on our panel, but the results were not (statistically) significant for all but one sector. These estimates are therefore not discussed here but are available upon request.

For each sector, the marginal elasticity of output with respect to capital and labor can be derived as

$$\varepsilon_K^i = \frac{\partial \ln Y_i}{\partial \ln K_i} = b_1 + b_3 \ln L_i \tag{2}$$

$$\varepsilon_L^i = \frac{\partial \ln Y_i}{\partial \ln L_i} = b_2 + b_3 \ln K_i \tag{3}$$

Then marginal products, MPK and MPL, are given by

$$\mathrm{MP}K^i = \frac{Y_i}{K_i}\varepsilon_K^i \tag{4}$$

$$\mathrm{MP}L^i = \frac{Y_i}{L_i}\varepsilon_L^i \tag{5}$$

Note that Eqs. (2)–(5) imply that marginal products are decreasing in their own inputs (i.e., diminishing) and increasing in the other input.

The marginal rate of (technical) substitution (MRTS) measures the rate at which the factors of production can be interchanged while holding output constant; it simply equals the ratio of the marginal products:

$$\mathrm{MRTS}_{K,L}^i = \frac{L_i}{K_i}\frac{\varepsilon_K^i}{\varepsilon_L^i} \tag{6}$$

It can be shown that the scale elasticity is the sum of all input elasticities:[4]

$$\mathrm{SE}_i = \varepsilon_K^i + \varepsilon_L^i = b_1 + b_2 + b_3 \ln(L_i \cdot K_i) \tag{7}$$

Finally, the elasticity of substitution between inputs is

$$s_i = \frac{\varepsilon_K^i + \varepsilon_L^i}{\varepsilon_K^i + \varepsilon_L^i + 2b_3} \tag{8}$$

which depends on the levels of both K_i and L_i.[5]

[4] See, for example, Vinod (1972).

[5] Since our goal here is extending the empirical literature on the textile industry, we keep the discussion of theoretical issues to a minimum and omit any derivations. The interested reader is referred to the classic theoretical papers by Lu and Fletcher (1968), Sato and Hoffman (1968), Revankar (1971), Christensen et al. (1973), and Lovell (1973). For a discussion of empirical issues involved in applications of VES functions, see Vinod (1976).

3 Econometric model

The basic estimable model is obtained by taking the natural log of Eq. (1):

$$\ln Y_{it} = b_0 + b_1 \ln K_{it} + b_2 \ln L_{it} + b_3 \ln K_{it} \ln L_{it}$$

which, in terms of a panel regression equation, becomes

$$\ln Y_{it} = \beta_i + \gamma_t + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln K_{it} \ln L_{it} + v_{it} \tag{9}$$

where

Y_{it} is real output of sector i in period t,
K_{it} is capital stock employed by sector i in period t,
L_{it} is a measure of labor input in sector i in period t,
β_i is a sector-specific intercept term,
γ_t is a period-specific trend factor,
v_{it} is the error term, which may include a random component in addition to a pure white noise term.

Equation (9) can be used to accommodate a wide range of models by applying the appropriate restrictions. For example, constraining $\beta_i = \beta_0$ for all i, $\gamma_t = 0$ for all t, and assuming that v_{it} is pure white noise, produces a pooled regression, which can be estimated by ordinary least squares (OLS). Alternatively, $\beta_i = \beta_0$ and $v_{it} = u_i + \epsilon_{it}$ yields a two-way random effects model.[6]

4 Data

Our sample is drawn from the NBER Manufacturing Productivity Database (Bartelsman and Gray 1996). It covers all 23 four-digit SIC textile sectors over the period 1958–1996. The data include observations on values of shipments (i.e., sales), real capital stock (including plant and equipment), and various measures of labor inputs, such as total number of workers, numbers of production and non-production workers, hours, etc. The data also include implicit price deflators for variables measured in nominal terms, such as value of shipments and cost of materials.

For output, we use real value added. Although the data provide value added figures for each sector and each year, they are in millions of current dollars (i.e., nominal terms). Therefore, we construct the real value added series for each sector by separately deflating the value of shipments (VISHIP) and cost of materials (MATCOST) using the appropriate price indexes, and then taking the difference. Figure 1 shows the plot of this construction along with the value

[6] See Greene (2000) or any other standard econometrics text for further description of panel data models.

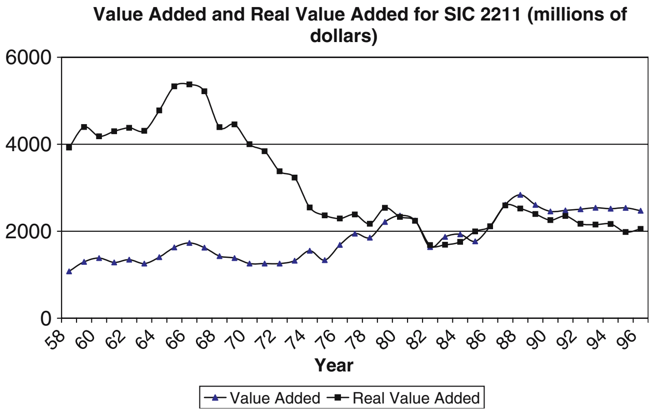

Fig. 1 Real and nominal value added for SIC 2211

added measure contained in the dataset for SIC 2211.[7] The apparent upward trend in the nominal measure throughout the period is clearly caused by rising prices rather than increases in the output itself. The natural log of real value added is our dependent variable.[8] The coverage of our panel dataset is shown in Table 1.

For L we use total number of production workers, PRODE, as it appears to be the most adequate measure of the labor input involved in the actual production. An alternative approach is to use total workers, but this would include nonproduction labor (i.e., management), which has not changed much in recent years (Christoffersen and Datta 2004).[9] We use the natural log of the number of production workers; in our regressions it appears as $\ln L$. Similarly, for capital we use $\ln K$, which is the natural log of total value of capital.

5 Estimation results

5.1 One-way fixed and random effects models

We estimate the one-factor fixed (FEM) and random effects models (REM) on our panel. The results are summarized in the two right-most columns of

[7] Comparison of other sectors yielded very similar results and are nor reproduced here but are available from the authors upon request.

[8] This computation of real value added resulted in several negative values, which were discarded yielding 881 usable observations.

[9] A possible future extension of this research may consider two types of labor – production and nonproduction – and estimate the degree to which they are substitutable.

Table 1 Panel data coverage

SIC	Number of years in sample	Period(s) covered
2211	39	1958–1996
2221	39	1958–1996
2231	39	1958–1996
2241	39	1958–1996
2251	39	1958–1996
2252	39	1958–1996
2253	39	1958–1996
2254	39	1958–1996
2257	34	1961–1963, 1966–1996
2258	31	1966–1996
2259	39	1958–1996
2261	39	1958–1996
2262	39	1958–1996
2269	39	1958–1996
2273	39	1958–1996
2281	39	1958–1996
2282	39	1958–1996
2284	39	1958–1996
2295	39	1958–1996
2296	37	1958–1974, 1977–1996
2297	39	1958–1996
2298	39	1958–1996
2299	39	1958–1996
Total	881	

Table 2.[10] The results of simple OLS estimation are also presented for comparison.

The individual sector-specific intercept terms for the FEM are all positive, significant at the 1% level and range from 3.277 for Tire Cord and Fabrics to 5.297 for Knit Outerwear Mills; they are not displayed here out of space considerations.

It is clear from the estimation results that the FEM/REM approach is appropriate and superior to OLS. The likelihood ratio (LR) and lagrange multiplier (LM) tests confirm this – the single constant-term specification is rejected.[11] Therefore, we conclude that there are substantial systematic differences in the production processes across textile sectors.

[10] We assume that the sector effects are exogenous and are uncorrelated with other righthand-side variables (the inputs). It is possible that a firm's choice of inputs is affected by the realization of its effect; however, we do not believe this issue is of concern in the present context. Our data are at the sector level, not firm or plant level, so input mix decisions should not be affected by the sector's effect. Also, we assume that inputs are strictly exogenous with respect to the error term. We thank the Associate Editor for directing our attention to this issue.

[11] The LR χ^2 statistic is 382.89; the Breusch–Pagan test yields a LM χ^2 statistic of 1059.3; both are highly significant.

Table 2 OLS, one-factor fixed and random effects results

	OLS	FEM	REM
Constant	3.5978		4.068
	(10.485)		(5.756)
$\ln L$	−0.3723[a]	−2.1811	−1.807
	(2.484)	(6.659)	(6.387)
$\ln K$	0.2741	0.3523	0.3905
	(4.731)	(2.899)	(3.712)
$\ln K \times \ln L$	0.0954	0.2942	0.242
	(5.055)	(6.642)	(6.368)
R^2	0.5339	0.6982	
F^{b}	334.86	79.12	

$N = 881$. Absolute value t-statistics in parentheses

[a] Significant at the .05 level All other coefficients are significant at the .01 level

[b] Numerator and denominator degrees of freedom for the F-statistic are: for OLS (3, 877), for FEM (25, 855)

Selecting between the fixed- and random-effects specifications is a slightly more difficult task. A priori, we hypothesize that the REM is more appropriate since individual sectors may respond in similar ways to unobserved industry-wide productivity shocks, whereas the FEM only allows for *fixed* changes in levels. On the other hand, the random effects specification requires that the sector-specific disturbances be uncorrelated with other variables in the model – the inputs – an assumption we have made above, but this may not, in fact, be true.[12] The Hausman test, based on the the difference of the two estimators – least squares dummy variables (LSDV, i.e. FEM) and generalized least squares for REM – provides one approach to settling this. The test statistic is 24.21, which has a chi-squared distribution with 3 degrees of freedom. The test rejects the REM specification in favor of fixed effects.

A potential problem in the estimations above is the correlation of the residuals within each sector across periods. The estimated autocorrelation coefficient is reported as 0.82 for our fixed effects model, which is quite high. A usual correction for autocorrelation using the Prais-Winsten algorithm as well as the Cochrane-Orcutt procedure was attempted for both the FEM and the REM specifications, but neither led to significant results as the standard errors of the estimates became large.[13]

A more direct approach to dealing with cross-period correlation is to model it directly, which is discussed in the next section.

[12] As an example, consider a surge in energy prices – an industry-wide shock – which causes firms to change their input mix.

[13] We attempted a more formal test for serial correlation in the residuals using the Durbin–Watson statistic for panel data as described in Baltagi (1995, p. 94). The test uses residuals from the within estimator and confirms the presence of positive autocorrelation in our model. However, we find below that a two-factor FEM is preferable to the one-factor models presented in Table 2, and we use those results for our subsequent calculations (see Sect. 5.2).

5.2 Two-way fixed and random effects

The following two-factor fixed effects model was estimated:

$$\ln Y_{it} = \beta_0 + \beta_i + \gamma_t + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln K_{it} \ln L_{it} + \epsilon_{it} \qquad (10)$$

Note that the model includes an overall constant term as well as sector-specific terms and period-specific effects. To avoid collinearity, the following restrictions are imposed:

$$\sum_{i=1}^{23} T_i \beta_i = 0 \qquad (11)$$

and

$$\sum_{t=1}^{39} N_t \gamma_t = 0 \qquad (12)$$

where T_i is the number of observations (periods) in group i, and N_t is the number of sectors observed in period t. The restrictions in Eqs. (11) and (12) ensure that the presence of the overall constant term does not cause a "dummy variable trap."[14]

Because of several deletions, a few of the sectors are observed at less than the full 39-year period.[15] The estimation results are presented in Table 3.

The full two-way specification – including sector- and time-specific effects, and the other RHS variables – is preferred over the restricted specifications; in particular, the null of the one-way FEM is rejected with a LR statistic of 618.57. The Hausman test yields a test statistic of $\chi^2_{\text{df}=3} = 26.95$, which is highly significant at the 1% level, indicating that the fixed-effects specification is preferable to random effects. The full tables of estimates of β_i and γ_t are omitted due to limited space. However, two aspects emerge as worthy of note. First, SIC 2251 (Women's Full-length and Knee-length Hosiery) yields a negative and larger-than-average in magnitude intercept coefficient suggesting this sector's productivity is low relative to other textile sectors. This observation is consistent with evidence of sharply declining demand for this sector's output, especially in the 1990s.[16] Second, the time effects reveal an obvious industry-wide adverse

[14] An alternative (and equivalent) approach is to omit the overall intercept and one of the period dummies. However, this creates an asymmetry since the the sector effects become sector-specific intercepts, while the time effects are contrasts to the omitted period. Therefore, we retain the overall constant term and all of the sector and time effects.

[15] See Table 1. Incidentally, this made estimation of a more general time series-cross section (TSCS) model not possible since it requires a balanced panel.

[16] See Marlow–Ferguson (2001, pp. 167–168). The "barelegged look" (wearing no stockings) which became fashionable in the 1990s faced firms producing Women's Hosiery with several years of continuingly declining sales.

Table 3 Two-factor fixed effects results

Constant	6.149[a]
	(8.04)
$\ln L$	−0.107
	(0.327)
$\ln K$	−0.4858[a]
	(3.904)
$\ln K \times \ln L$	0.1776[a]
	(4.367)
R^2	0.769
$F_{63,817}$	43.18

Absolute value t-statistics in parentheses $N = 881$

[a] Significant at the 0.01 level

productivity shock around 1974 when $\hat{\gamma}_t$ is much lower than the estimates for neighboring periods. The shock probably reflects the effects of the energy crises in the 1970s.

6 Marginal productivity of inputs, elasticities of scale and substitution

In order to obtain empirical estimates of the theoretical constructs in Sect. 2, we combine the estimated coefficients with the data series on inputs, K_{it} and L_{it}, and output Y_{it}. We employ the estimates from our two-factor FE specification as they provide the best overall fit to the data.

In the remainder of this section, we summarize our empirical results. We briefly discuss the observed patterns of individual input productivity and the elasticity of scale and then turn our attention to the elasticities of substitution for various sectors.

6.1 Marginal productivity of inputs

All sectors generally exhibited positive and rising MPLs over the entire sample period, although for Thread and handwork yarns (SIC 2284) it grew very little. This finding is consistent with reports of slower-than-average growth in wages in that sector.[17] All of the sectors experienced noticeable adverse labor productivity shocks in the early-to-mid 1970s, following a period of steady growth in MPL for most sectors in the 1960s. The 1980–1990 period is characterized by the same general upward trend, but with several minor "bumps."

Several sectors' MPK is negative throughout the period. While in the short run, this observation would signal overcapitalization by firms in these sectors, in the long run one would expect firms to adjust their levels of capital stock. Upon closer examination, it turns out that all of these sectors – Knitting Mills (SIC 2259), Coated Fabrics, not rubberized (SIC 2295), Cordage and Twine (SIC 2298) and Tire Cord (SIC 2296) – experienced declining employment

[17] Under the assumption of perfectly competitive labor markets, workers in each sector are paid real wages equal to their marginal product.

during most of the sample period. This explains the continuously falling marginal product of capital.

We find that the sectors characterized by steadily increasing MPK are the ones faced with steadily growing demand. These are Hosiery (SIC 2252), Circular Knit Fabrics (SIC 2257) and Carpets and Rugs (SIC 2273). By contrast firms specializing in broad woven and narrow woven fabrics (SIC 2231 and 2241) such as cotton and wool have faced declining demand for a number of years, and their MPK falls throughout.

6.2 Elasticity of scale

The scale elasticity series for each sector was constructed as the sum of the marginal elasticities of factors. This relationship allows us to determine whether changes in the elasticity of scale are driven primarily by changes in labor productivity or that of the capital stock.

Overall, the elasticity of scale values range from −0.147 for Knitting Mills (SIC 2259) in 1958 to 1.91 for Broadwoven fabric Mills, cotton (SIC 2211) in 1967. In other words, there is evidence of decreasing, constant, and increasing returns across sectors; furthermore, for some sectors substantial changes occur over time. Significant increases in scale elasticity parameters were observed for 10 of the 23 sectors, although some of these increases were modest. Several sectors saw growth in the scale elasticity until the mid-1970s and modest decline thereafter.

These results are consistent with those reported for the industry as a whole for a similar period by Ramcharran (2001). He finds, for example, that the overall scale elasticity grew from 0.094 to 1.638 between 1975 and 1993. Additionally, we find that the observed increases on the returns-to-scale are largely due to increasing marginal elasticity of labor (and, consequently, MPL) rather than increasingly productive capital, which also agrees with previously cited results. The sector-level analysis, however, sheds additional light on the intraindustry developments.

6.3 Elasticity of substitution

The estimated elasticity of substitution values are somewhat higher than those found in previous studies. Our estimates for most sectors lie in the 0.6–0.8 range, while the values found in the literature rarely exceed 0.25.[18] Nevertheless, our results are consistent with the theoretical expectation of negatively-sloped isoquants ($s < 1$), as well as with the empirical regularity of observing elasticities of substitution in the (0, 1) interval.[19]

[18] See Ramcharran (2001) and other studies cited in that paper.

[19] The constructed series for each sector are presented graphically in Sect. 9.3.

More importantly, however, we find substantial differences in the magnitudes and variation (i.e., patterns or direction of change) in the elasticity of substitution across sectors. Ten sectors exhibited rising s, albeit all but two of them were rather modest increases. The largest increases were observed for Lace and warp knit fabric mills (2258) and Nonwoven fabrics (2297). For Lace and warp knits, this observation appears consistent with the conduct and performance of the firms: following the adoption of GATT, many producers moved their operations to Mexico, where labor is relatively more abundant while capital is not. Thus, the two factors appear quite interchangeable there. The Nonwovens, on the other hand, are quite a puzzle: the sector is relatively capital-intensive as the production of these fabrics requires mechanical, chemical or thermal bonding of individual yarns. We take a closer look at Nonwoven fabrics in the last section.

Five other sectors had declining elasticities, with three of them falling substantially. The two largest declines were observed for Knit underwear and nightwear mills (2254) and Tire cord and fabrics (2296). Thus, there is significant support for the use of a variable elasticity production function.

Overall, fewer sectors displayed declines in their substitution elasticity parameters than did increases. On the other hand, the declines were bigger in magnitude (on average) than the corresponding increases. This is consistent, once again, with the overall pattern of declining substitutability between factors in the textile industry. In other words, it appears that greater reliance on the capital input by at least some sectors in the recent years has made the two factors less substitutable.

These results also imply that industry-wide policy conclusions may not be appropriate, given the sectoral differences observed. For example, previous studies of textiles which found declining substitution elasticity values[20] conclude that the industry uses mostly labor-saving (or capital-using) technology. This in turn implies that many textile jobs are lost to technological progress and not necessarily to low-wage foreign competition. Given our findings, such conclusions are not so obvious for the industry as a whole.

7 Validity of VES results

To check the validity and robustness of our estimates obtained with the VES function, we also estimated a Cobb–Douglas and a CES function on our panel. The C-D function does not fit the data well, as the estimate of the elasticity of output with respect to capital is negative and barely statistically significant at the 10% level (See Table 4).[21] The results of the CES estimation are shown in Table 5 in Sect. 9.2. The computed elasticity of substitution from the CES function is 0.6. While this is comparable to the range of estimates for s we obtained

[20] See Batavia (1979), Williams (1984), and Ramcharran (2001).

[21] Of course, the significance of the estimated coefficient on the $(\ln K \cdot \ln L)$ term in Tables 2 and 3 strongly suggests that the C-D function is not adequate.

from the VES function (0.6 – 0.8), there is clear evidence of changing elasticity of substitution over time.[22]

8 Summary and concluding remarks

Estimation of the VES production function with panel data techniques takes full advantage of between- and within-sector variations. We find that there are substantial differences in the evolution of the production processes in different textile sectors, something industry-level analysis cannot uncover.

In particular, we find that sectors differ in the levels and behavior (over time) of marginal productivity of labor and capital, their ability to achieve minimum efficient scale, and the degree of substitutability between inputs. For example, negative and sometimes falling MPK indicates that the industry has overinvested in capital.

With respect to the economies of scale, sectors with products that have experienced growing demand in recent years tend to have higher and faster-growing elasticities of scale. Conversely, those sectors faced with declining demand (and falling output) have lower values of scale elasticity.

Our estimates of the elasticities of substitution are somewhat higher than the overall values reported previously for textiles as an industry. Moreover, for several sectors, the substitution elasticity parameters actually rose, indicating greater substitutability between labor and capital. While this may be consistent with the notion of a "declining industry" for some sectors, it appears rather puzzling for, say, Nonwovens, widely touted as the fastest growing textile sector and the future of the industry (Marlow-Ferguson 2001).

Some of the most pressing issues facing U.S. textile firms today are employment-related. Job loss throughout the industry is evident and is frequently blamed on the low-wage competition from abroad, particularly countries in Asia. On the other hand, declining employment is precisely what has allowed many textile firms to remain productive in the 1990s. For those sectors characterized by increasing factor substitutability, import competition poses a very real threat. This is especially true given increasingly open trade between countries of North America (due to NAFTA) as well as elsewhere. Other sectors, where capital and labor are becoming less substitutable should not be as affected by low-wage competition and should use this to their advantage – develop sophisticated technology and train workers to become productive at using it.

8.1 Nonwoven fabrics

What makes the nonwoven fabric industry unique is its relatively strong growth – in terms of employment, wages, and output, as well as in the number of

[22] We also considered estimating a CES function separately for each sector to obtain sector-specific substitution elasticities, but such results would not be directly comparable with the variable elasticities. Furthermore, splitting the panel into individual sectors discards all of the information on industry-wide shocks contained in the data.

firms engaged in production – while most of the textile sectors are faced with declining demand and increased foreign competition. New uses for nonwovens continue to be developed. On the other hand, the relative capital intensity of the production process virtually makes nonwoven fabrics immune to much of the competition from abroad: the governments of developing countries, whose prime objective is finding employment for its labor force, tend to avoid subsidizing such industries requiring large capital investments and small work force.

The output of the U.S. nonwoven sector grew through 1997. The industry employed over 11,000 workers at average wages above the typical rates for textiles. The marginal productivity of labor grew especially fast in the late 1970s and early 1980s. The marginal product of capital, on the other hand, remains negative indicating that perhaps investment still outpaced the growth in other factors and output. At the end of the sample period, the industry is operating in the increasing-returns-to-scale range (its scale elasticity grew from 0.62 in 1958 to 1.2 in 1996). This is consistent with the description of a capital-intensive sector, where production involves large fixed costs.

Substitution between labor and capital has increased, albeit modestly, from 0.62 to 0.76 over the 39-year period. While this is somewhat unusual for a production process requiring very specific machinery, it may be indicative of the technological developments that took place since the early 1960s giving firms greater flexibility in the choice of technological methods to employ in production.

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9 Appendices

9.1 List of SIC codes

SIC	Name
2211	Broadwoven fabric mills, cotton
2221	Broadwoven fabric mills, manmade fiber and silk
2231	Broadwoven fabric mills, wool (including dyeing and finishing)
2241	Narrow fabric and other smallwares mills: cotton, wool, silk and manmade fiber
2251	Women's full-length and knee-length hosiery, except socks
2252	Hosiery, not elsewhere classified
2253	Knit outerwear mills
2254	Knit underwear and nightwear mills
2257	Weft knit fabric mills
2258	Lace and warp knit fabric mills
2259	Knitting mills, not elsewhere classified
2261	Finishers of broadwoven fabrics of cotton
2262	Finishers of broadwoven fabrics of manmade fiber and silk
2269	Finishers of textiles, not elsewhere classified
2273	Carpets and rugs
2281	Yarn shipping mills

SIC	Name
2282	Yarn texturizing, throwing, twisting, and winding mills
2284	Thread mills
2295	Coated fabrics, not rubberized
2296	Tire cord and fabrics
2297	Nonwoven fabrics
2298	Cordage and twine
2299	Textile goods, not elsewhere classified

9.2 Panel estimates of CD and CES production functions

The general form of the CD function we estimate is

$$Y_{it} = b_0 K_{it}^{b_1} L_{it}^{b_2} \tag{13}$$

Imposing the constant-renturns restriction $b_1 + b_2 = 1$, taking logs of Eq. (13) and rewriting we get

$$\ln Y_{it} = \beta_i + \gamma_t + \ln L_{it} + \beta_1 (\ln K_{it} - \ln L_{it}) + \varepsilon_{it} \tag{14}$$

Equation (14) is estimated with a two-way fixed effects OLS; the results are shown in Table 4. The estimates of sector and period dummies are omitted, but are available from the authors upon request.

The estimates imply a negative elasticity of output with respect to capital, so the CD specification is rejected.

Next, we estimate a constant elasticity (CES) function of the form

$$Y_{it} = \varphi \left(\delta K_{it}^{-\rho} + (1 - \delta) L_{it}^{-\rho} \right)^{-\frac{\nu}{\rho}} \tag{15}$$

Taking logs produces

$$\ln Y_{it} = \ln \varphi - \frac{\nu}{\rho} \ln \left[\delta K_{it}^{-\rho} + (1 - \delta) L_{it}^{-\rho} \right] \tag{16}$$

Table 4 Cobb–Douglas two-factor fixed effects results

Constant	3.4665[a]
	(7.525)
$\ln L$	(fixed)
$(\ln K - \ln L)$	−0.7106[b]
	(1.823)

Absolute value t-statistics in parentheses $N = 881$

[a] Significant at the 0.01 level

[b] Significant at the 0.1 level

Table 5 CES two-factor fixed effects results

Constant	4.1186[a]
	(8.311)
$\ln L$	1.9641[a]
	(8.372)
$\ln K$	−0.7964[a]
	(3.706)
$\ln^2(K/L)$	0.1155[a]
	(3.430)
R^2	0.767
F[b]	42.69

Absolute value t-statistics in parentheses $N = 881$

[a] Significant at the 0.01 level

[b] Degrees of freedom (numerator and denominator) for the F-statistic are 63 and 817

Kmenta (1967) showed that this CES function can be estimated using a Taylor series approximation around the point $\rho = 0$. If one estimates the following regression equation

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln^2 (K_{it}/L_{it}) + \varepsilon_{it} \tag{17}$$

then the parameters of (16) can be computed as nonlinear functions of the estimates (β's) obtained from (17). The needed transformations are

$$\begin{aligned} \delta &= \beta_1/(\beta_1 + \beta_2) \\ \nu &= \beta_1 + \beta_2 \quad \text{and} \\ \rho &= -2\beta_3(\beta_1 + \beta_2)/\beta_1\beta_2 \end{aligned}$$

Equation (17) is estimated by OLS with sector-specific and time dummies. The intercept term for sector i in period t is given by

$$\alpha_{0,it} = \beta_0 + \beta_{0,i} + \gamma_t$$

and the structural parameter φ_{it} from (15) is computed as

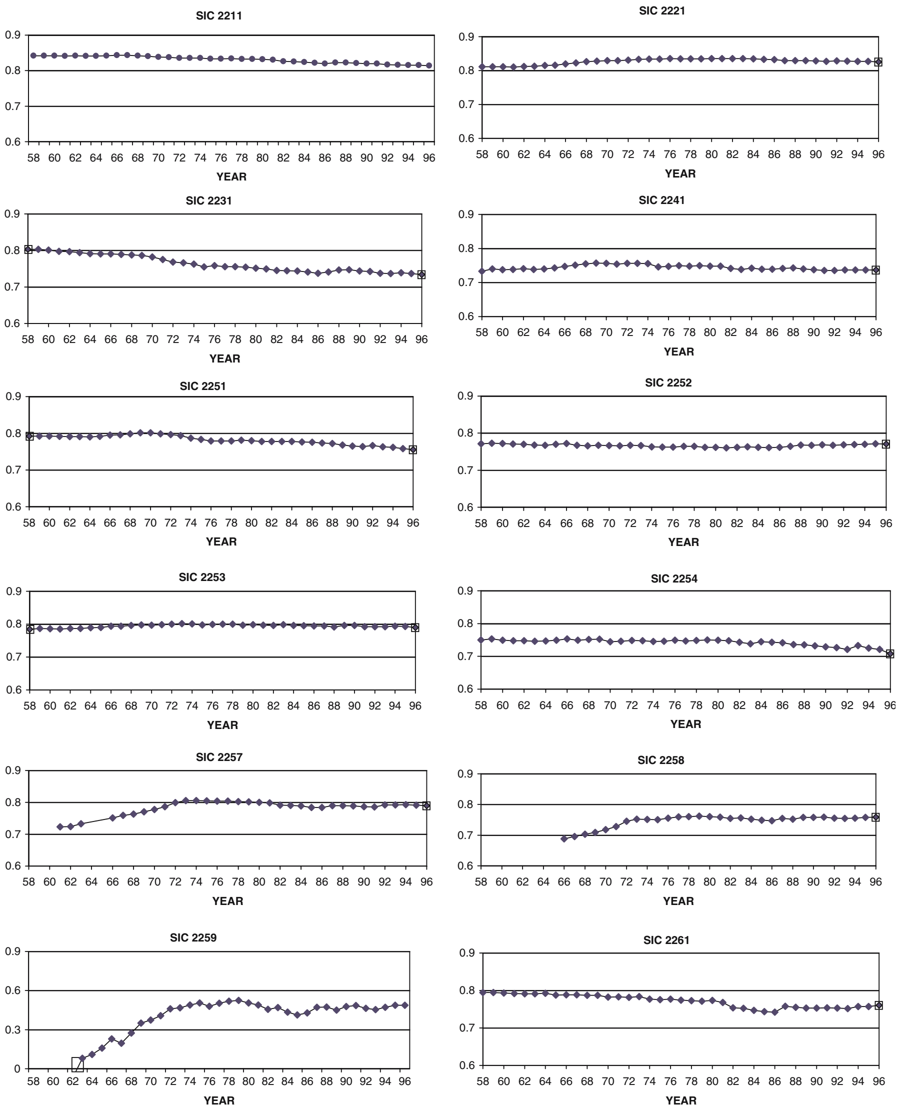
$$\varphi_{it} = e^{\alpha_{0,it}}$$

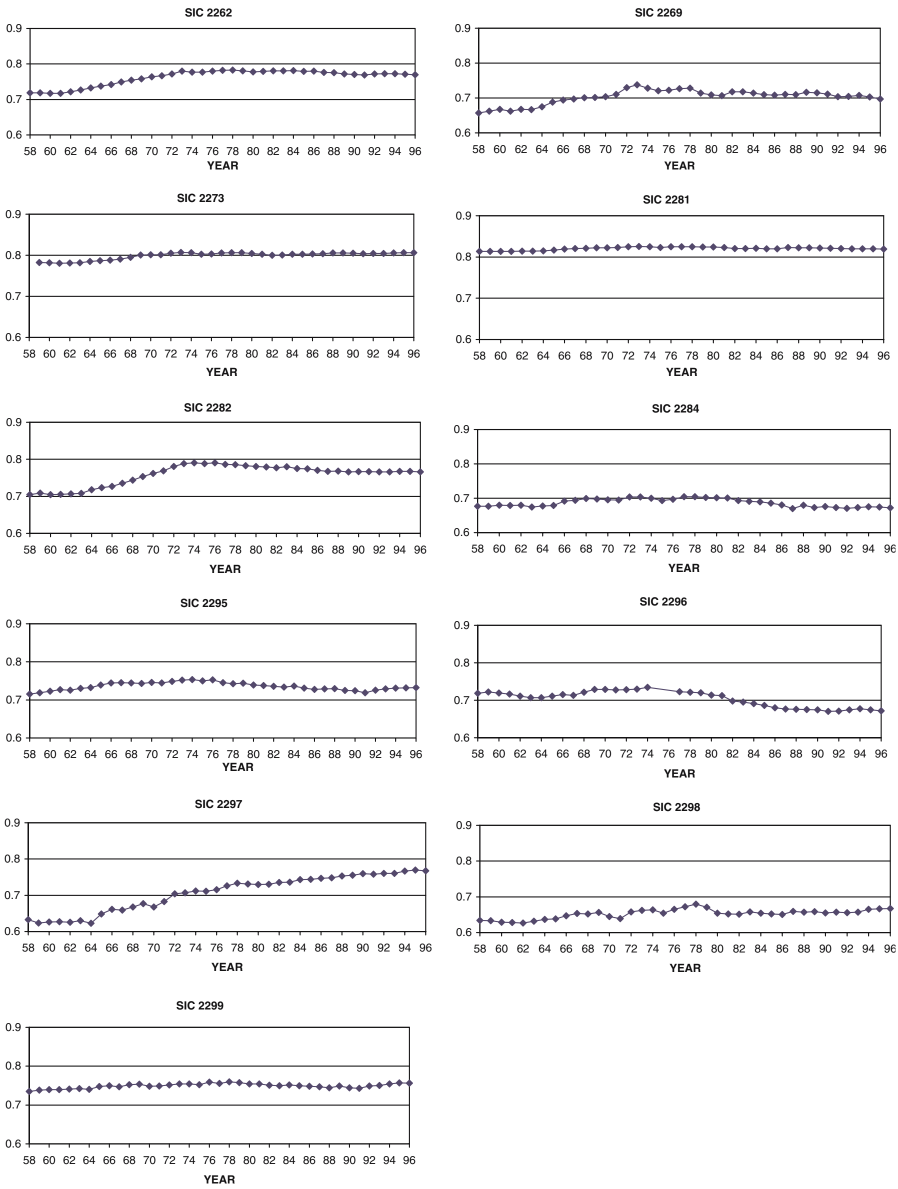
The estimated coefficients are displayed in Table 5.

These estimates imply an estimated value of ρ of 0.6651. Therefore the estimated (constant) elasticity of substitution between capital and labor is

$$\frac{1}{1+\rho} = 0.6 \tag{18}$$

9.3 Estimated elasticity of substitution




SIC 2262
SIC 2269
SIC 2273
SIC 2281
SIC 2282
SIC 2284
SIC 2295
SIC 2296
SIC 2297
SIC 2298
SIC 2299
0.9
0.8
0.7
0.6
58 60 62 64 66 68 70 72 74 76 78 80 82 84 86 88 90 92 94 96
YEAR

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